Question 2.3: Why do the “Cubans” have no comparison group? Explain in the context of the study.

This is beacuase the amount of cubans living inb the other cities is not enopugh to gather data on. Miami has a large cuban population, so this makes sense.

Question 2.4: Unemployment after the Mariel boatlift goes up for all groups, rising from 5.0% in April 1980 to 7.1% in July. Why does Card argue that "there is no evidence that the Mariel influx adversely affected the unemployment rate of either whites or blacks" (p. 250)?

This might be because in other cities, the unemployment rate for these two demographics also follows the same pattern where Cubans are not as many outside of Miami.

Question 2.5: How much attention should we pay to the ups and downs in these graphs? Are these chance fluctuations from the sample survey ("noise"), or are they important information that we should pay attention to ("signal")?

1. The fluctuations doesn't seem arbitrary, so they are signal
2. The trend reverses very quickly and very suddenly, so they are just noises
3. We can't tell just by looking, but one could in theory (and with the help of a statistics course) quantify the magnitude of fluctuations that we would expect from random sampling.

Assign the number corresponding to your answer to q2_4 below.

In [23]:
```
q2_5 = 3
```

In [24]:
```
grader.check("q2_5")
```

Out[24]:
```
q2_5 results: All test cases passed!
```

0.1 Part 3: Wages

Now we will try to replicate Card's findings that the Mariel boatlift also had little or no effect on wages of natives. For simplicity we will not deflate the wages but instead consider the nominal wages.

Because some of the values in the `earnhre` column are missing (`nan`), we remove the rows where this is the case in the cell below. **Throughout this part, make sure you use `mariel_ehre` instead of `mariel`, or else your calculations may error.**

In [25]:
```
mariel_ehre = mariel[np.isnan(mariel["earnhre"]) == False].copy()
```

In order to make the wages more linear and to put them on an easier-to-understand scale, we take the natural log of each value in the `earnhre` column and store this as `log_w`.

```
In [26]: log_w = np.log(mariel_ehre["earnhre"]/100)
         mariel_ehre["log_w"] = log_w
         mariel_ehre.head(5)
```

```
Out[26]:     age     smsarank                 esr              ftpt79  earnhre    educ  \
         3    56  Los Angeles  Employed-At Work  Employed full-time    700.0      HS
         6    23  Los Angeles  Employed-At Work  Employed full-time   1002.0      HS
         16   65  Los Angeles  Employed-At Work  Employed full-time    895.0      HS
         32   61  Los Angeles  Employed-At Work         Employed PT    500.0      HS
         35   41  Los Angeles  Employed-At Work  Employed full-time    400.0  lessHS

            ethrace  year     log_w
         3   whites  1979  1.945910
         6   whites  1979  2.304583
         16  whites  1979  2.191654
         32  whites  1979  1.609438
         35  whites  1979  1.386294
```

We want to create a similar pivot table as in part 2, except we want the values in this table to be the mean of the log of wages. We create this table for Miami below, making sure to also filter `merial_ehre` for rows where the individual is employed full-time.

```
In [27]: miami_wages = mariel_ehre[(mariel_ehre["age"] >= 16) & \
                                   (mariel_ehre["age"] <= 61) & \
                                   (mariel_ehre["smsarank"] == "Miami") & \
                                   (mariel_ehre["ftpt79"] == "Employed full-time")]
         miami_wages_ethrace = pd.pivot_table(miami_wages, values="log_w", index=["year"], columns=["et
         miami_wages_ethrace
```

```
Out[27]: ethrace    blacks    cubans  hispanics    whites
         year
         1979     1.433196  1.435591   1.342982  1.664646
         1980     1.559940  1.455480   1.424821  1.740305
         1981     1.719957  1.579118   1.550045  1.818311
         1982     1.666419  1.606005   1.675179  1.879977
         1983     1.678183  1.618799   1.638360  1.911506
         1984     1.782611  1.687249   1.750424  1.924276
         1985     1.860924  1.612961   1.808548  1.869408
```

Question 3.1: Create the same pivot table below, except for the comparison cities (that is, all cities *except for Miami*). Store the pivot table as `not_miami_wages_ethrace`.

```
In [28]: not_miami_wages = mariel_ehre.query("smsarank != 'Miami'") # select relevant rows
         not_miami_wages_ethrace = pd.pivot_table(not_miami_wages, values='log_w', index='year', column
         not_miami_wages_ethrace
```

Out[28]:

ethrace	blacks	cubans	hispanics	whites
year				
1979	1.548001	1.549578	1.494875	1.616494
1980	1.648242	1.570725	1.581087	1.704376
1981	1.724695	1.643614	1.671253	1.793804
1982	1.785104	1.671725	1.705705	1.858023
1983	1.812533	1.713596	1.730999	1.866775
1984	1.817027	1.701693	1.775909	1.917960
1985	1.829419	1.857165	1.778731	1.949227

In [29]:

```
grader.check("q3_1")
```

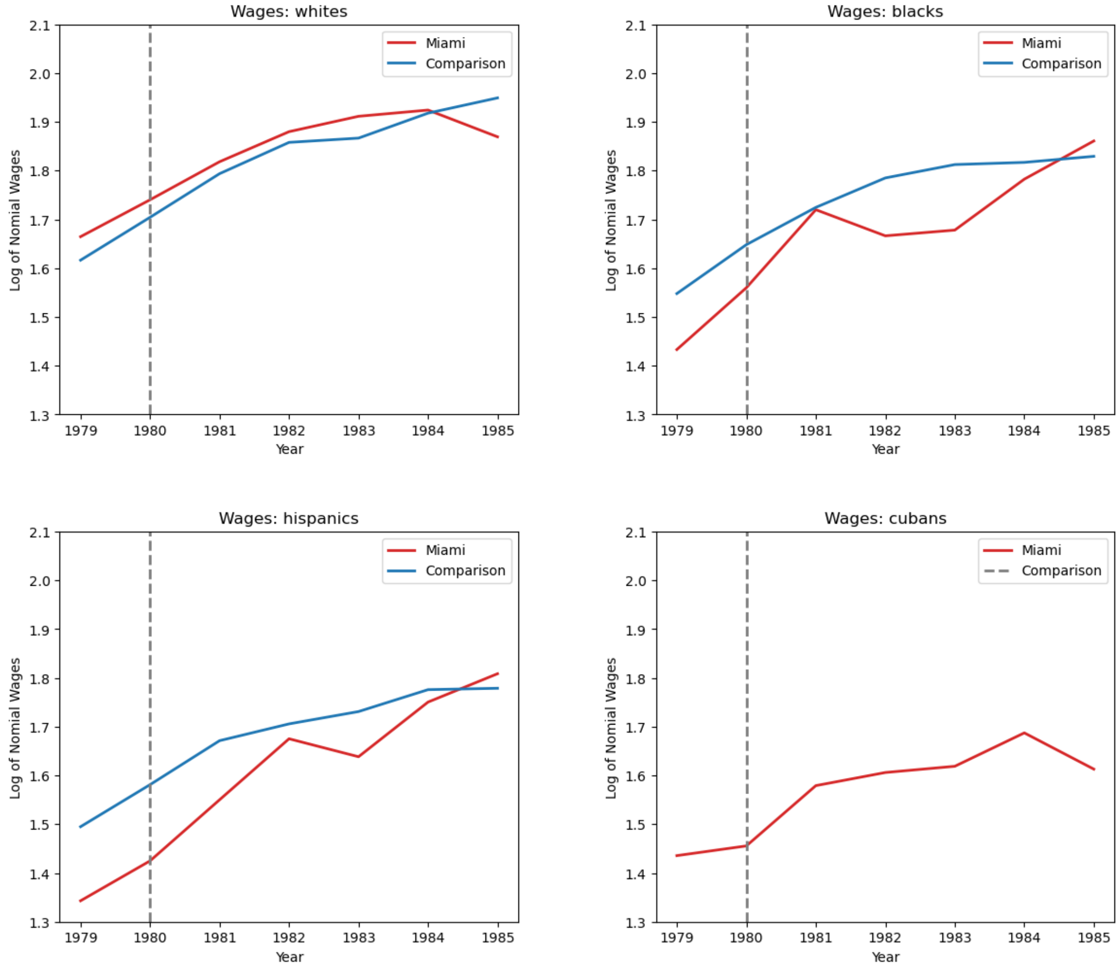
Out[29]:

```
q3_1 results: All test cases passed!
```

In the cell below, we plot the wages for Miami and the comparison cities for each `ethrace` value.

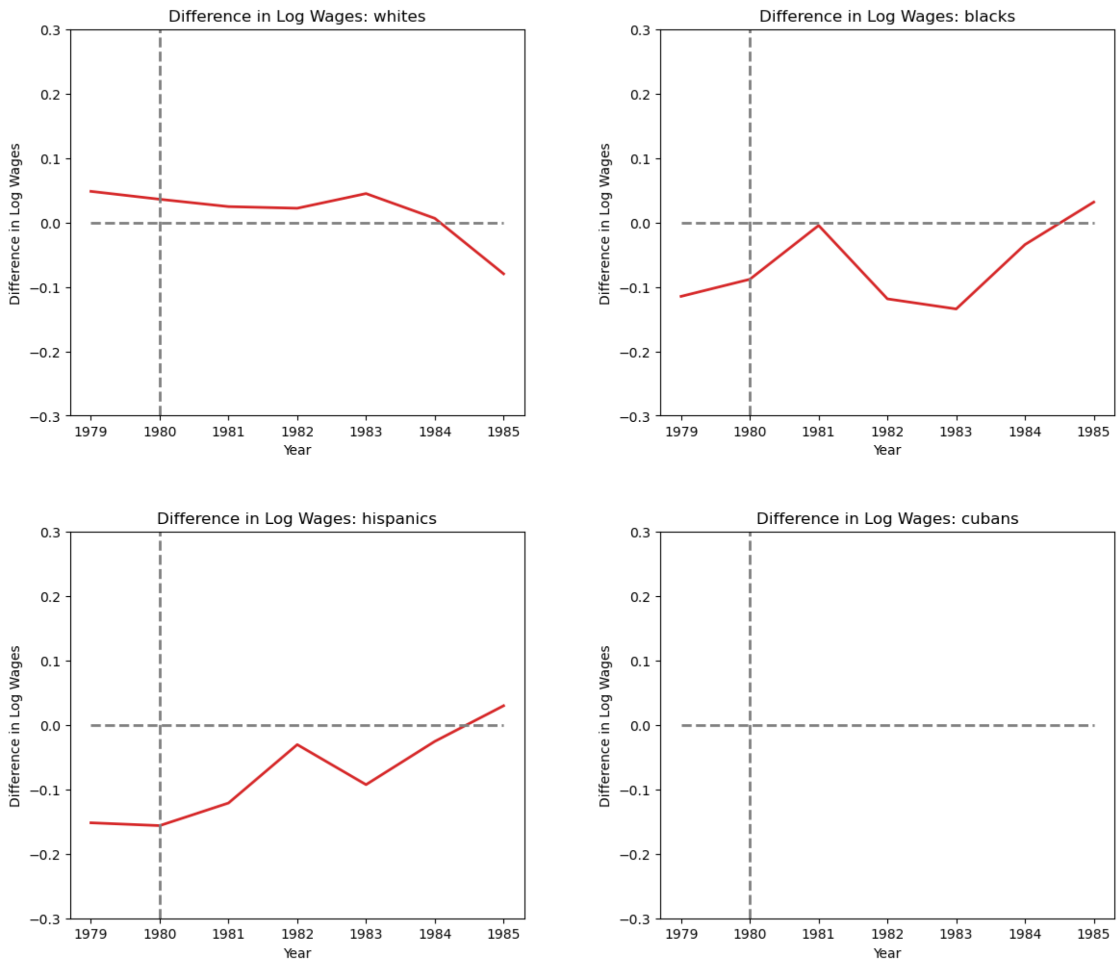
In [30]:

```
plot_wages_by_ethrace(miami_wages_ethrace, not_miami_wages_ethrace)
```



Our numbers differ from Card's Table 4 because we are not accounting for inflation. In order to make inferences about the effect of the boatlift on wages easier, let's plot the differences between Miami and the Comparison Cities. (The difference being plotted here is log wages for Miami *minus* log wages for comparison cities)

```
In [31]: plot_wage_diffs_by_ethrace(miami_wages_ethrace, not_miami_wages_ethrace)
```



Question 3.2: If wages were hurt by the influx of migrants, we would expect this graph to show

1. A decrease after 1980, as Miami wages went down relative to other cities
2. Values below 0 for all periods, because Miami would always have lower wages
3. An uptick after 1980 because we are working with logarithms.

Assign the number corresponding to your answer to `q3_2` below.

Hint: $\log A - \log B = \log \frac{A}{B}$

```
In [32]: q3_2 = 1
```

```
In [33]: grader.check("q3_2")
```

Out[33]: q3_2 results: All test cases passed!

So it seems that indeed our analysis is consistent with Card's conclusion that "the Mariel immigration had virtually no effect on wages or unemployment outcomes of non-Cuban workers in the Miami labor market" (p. 255).

0.2 Part 4: Education

We would expect any negative effect of the influx of immigrants to be strongest on the group that they most resemble. Because most of the Cuban immigrants in the boatlift were unskilled, we would expect the strongest effect on natives with the least education, with perhaps the clearest comparison group being Hispanics with the least education.

Card used a different approach, looking at the effects for low-skilled workers by predicting wages based on education and years of experience. Here we do something a bit simpler, using education only.

Question 4.1: If the boatlift had a negative effect on the employment of unskilled workers, what would we expect to see in the unemployment for each of categories of education in both Miami and the comparison cities?

Note: The possible values of `educ` are `BA`, `HS`, or `lessHS`.

For higher education, such as peope with a college dfegree(BA), we would see unemployment not vary that much. However, with people that only have a high school diploma(HS) or not(lessHS), we can see them being impacted more, so the unemployment rate will rise more in these categories.

Question 4.2: What happens to the unemployment rates of those with a college education (BA) between 1980 and 1982, when the effects of the Mariel boatlift should have been felt? What happens to those with the least education? ("lessHS"). Is this consistent with a large effect of immigration on the least educated that is hypothesized above?

For BA people, unemployment actually goes down and decreases. We see the opposite with less education. This does back up our claim previously.

Question 4.4: Like Card's study, many empirical works find very small or no impact of immigration on local workers' wages and employment. Several studies even found positive impact of skilled immigration on wages and employment. What are 2 possible reasons that having immigrants would benefit the native-born workers?

Having immigrants would benefit natives by opening other opportunities such as translators and tour guides and such for people who don't speak english. Also, it could add more diversity.